From Punch Cards to Prompt Engines: The Shared History of Artificial Intelligence and the Learning Sciences

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Abstract

Generative AI, in form of Large Language Models such as ChatGPT, has created a significant disruption in educational environments; however, the development of artificial intelligence and education as a field has a rich and storied history. This paper articulates the development of artificial intelligence in education with respect to several periods of development, as well as two major modes of thought, cognitivism and constructionism. The paper argues that these two modes of thought defined the landscape of artificial intelligence and that not only has education been a significant point of research in this field, but that learning was inextricably linked to the study of artificial intelligence: the early artificial intelligence researchers, such as Marvin Minsky, Seymour Papert, Herbert Simon, and Allen Newell, developed theories of thought and cognition and built these theories into applications of artificial intelligence and computing; these theories, with particular reference to the work of Minsky and Papert, would directly lead to the development of the learning sciences as a field of research. The paper also provides descriptions of several periods of bust-and-boom within the study of artificial intelligence, a brief review of the status of artificial intelligence in education as a field today, and an analysis of the use of artificial intelligence as a representation of human thought patterns in contemporary research.

Keywords: Artificial Intelligence, Artificial Intelligence in Education, Learning Sciences, Human-AI Collaboration, Constructionism, Cognitivism

Introduction

The histories of artificial intelligence (AI), artificial intelligence in education (AIED), and the Learning Sciences are complex, dramatic, and inextricably intertwined: one cannot be studied without the review of the other. However, contemporary models of AI have diverged from many of the perspectives and models of the past; the study of learning and of AI has separated. This separation, and its historical roots, will be further expanded on the findings section of this paper. This study, through the analysis of historical and seminal works in the fields of AI, AIED, and the Learning Sciences, tracks the development of these fields and argues for a return of the Learning Sciences theories, methodologies, and frameworks towards AI and AIED as generative AI models, such as ChatGPT, have emerged and disrupted the educational landscape. These historical frameworks have significant implications for current work in AIED and the Learning Sciences as they relate the two fields through their common theories and provide potential for future research to re-integrate Learning Sciences and AIED. This paper addresses two research questions: RQ1: How has the historical study of AI been influenced through pedagogy and learning sciences? and RQ2: How have these periods of historical study influenced the scope and volume of academic research on the topic?

The conception of AI itself dates to the mid-1950s with Alan Turing's (1950) *Computing Machinery and Intelligence*, and then was given its name at a series of workshops in Dartmouth College by John McCarthy (Williamson & Eynon, 2020). This paper argues that two competing theoretical frameworks, cognitivism and constructionism, have defined the AI and AIED landscapes since the Dartmouth workshops. Throughout the historical study of AI, education, learning, and psychology were critical components as the artificial modes of thought and applications being created were intended to reflect the modes of human thought.

While tools such as Large Language Models (LLMs) have dramatically increased the performance of AI models, many theories and studies have been used in the analysis and application of tools similar to this. Notable in this study is the conceptualization of AI as an

analogy to human intelligence and how the research on AI in education has shifted away from this framework, as well as tracing the application of Papert's *Constructionism* throughout AIED, the roots of behaviourism in Intelligent Tutoring agents, and the role of "summer" and "winter" (Toosi, 2021, p. 2) cycles in AI research.

Positionality

As a researcher, my positionality is shaped by my life experiences, backgrounds, and perspectives. I am a doctoral student in the learning sciences, balancing my academic pursuits with a full-time job and family responsibilities. As well, my professional background in both education and data science influences my interest in studying the intersection of technology and learning. I acknowledge that these factors may affect my approach to research, including the framing of research questions and interpretation of data. In placing myself in the debate that is described in the findings section, between the highly structured cognitivism or holistic constructionism, I would describe myself in the constructionist paradigm, or as Kolodner (2002) would describe, a "scruffy" (p. 139), representative of traditional perspectives in the learning sciences.

Methodology

This analysis was completed through a narrative state-of-the-art review methodology during my doctoral studies. This review describes the historical development of theory associated with AI and the Learning Sciences and potential future avenues for development (Sukhera, 2022). Sources were identified iteratively, determined by relevance, total citations, and citation networks which emerged through the study. Research articles were found through a variety of sources: major journals were identified and reviewed, including the *International Journal of Artificial Intelligence in Education, Computers and Education: Artificial Intelligence*, the *British Journal of Educational Technology,* the *International Journal of Computer-Supported Collaborative Learning*, the *International Journal of Educational Technology in Higher*

Education, and the *Journal of Computer-Assisted Learning.* As well, key scholars and articles were further identified through a discovery process based on the citations and reference lists in the initial articles identified, and the critical works of these scholars were further identified through the use of Google Scholar's citation count. To review historical trends in AI, the contemporary researchers were reviewed for references with particular respect towards the work of Williamson & Eynon (2020), Rismanchian and Doroudi (2023), and Doroudi (2023). These works provided significant exploratory sources for this analysis.

To complete the assessment of popularity of AI in academic research, the *OpenAlex* repository and API were used, provided by Aria et al. (2024). This analysis reviewed the specific use of the term "Artificial Intelligence" in the titles of academic articles by year as an approximation to the concept's popularity in research. Notably, the repository had sources starting at 1960 and thus popularity in the initial period of AI research, 1955-1960, was unable to be estimated with this method. Both the API query and data visualizations were created in R using the openalexR and ggplot packages; the code is provided in Appendix A.

Findings

This section examines the periods of growth and decline in the study of AI. There have been several notable periods in the study of AI, including the initial history of AI, the growth of cognitivism and constructionism, the first AI winter, the introduction of expert systems and the development of the Learning Sciences, the second AI winter, and the information age and machine learning revolutions. This section will describe the major perspectives and development of the field during these periods through analysis of the seminal works, as well as use the OpenAlex repository to estimate the growth of AI as a field through the use of the phrase in academic article titles.

Initial Development: 1950s and the Dartmouth Workshops

The initial growth period of the AI paradigm would be based primarily on the works of

Turing (1950) and McCarthy et al. (1955). Williamson and Eynon (2020) wrote that “Histories of AI stretch back at least as far as the birth of computer science… in the 1940s” (p. 223). One of the primary papers that has been noted is Alan Turing’s (1950) *Computing Machinery and Intelligence,* in which Turing (1950) created the original *Turing Test*, which describes the process in which we may assess if a machine can replicate a believable human mind. In this, he notes “The reader must accept it as a fact that digital computers… can in fact mimic the actions of a human computer very closely” (p. 438). Turing’s (1950) work is credited as the foundation of AI, though the author would not use the term *Artificial Intelligence*; this term would come later, with John McCarthy in a series of Dartmouth workshops.

McCarthy et al. (1955) would be the first to use the term, with the following contained in the proposal: “We propose a study… of artificial intelligence. The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it” (McCarthy et al., 1955, p. 1). This is the first recorded use of the term (Williamson & Eynon, 2020). The authors reference artificial neural networks (ANN) as well as abstractions, self-improvement, and randomness, which would become, and remain, critical foundations of AI research. In McCarthy’s Dartmouth workshop, we would see three researchers become critical to both the development of AI and educational theory – Herbert Simon, Allen Newell, and Marvin Minsky (Doroudi, 2023). These researchers became seminal figures in the following periods of development.

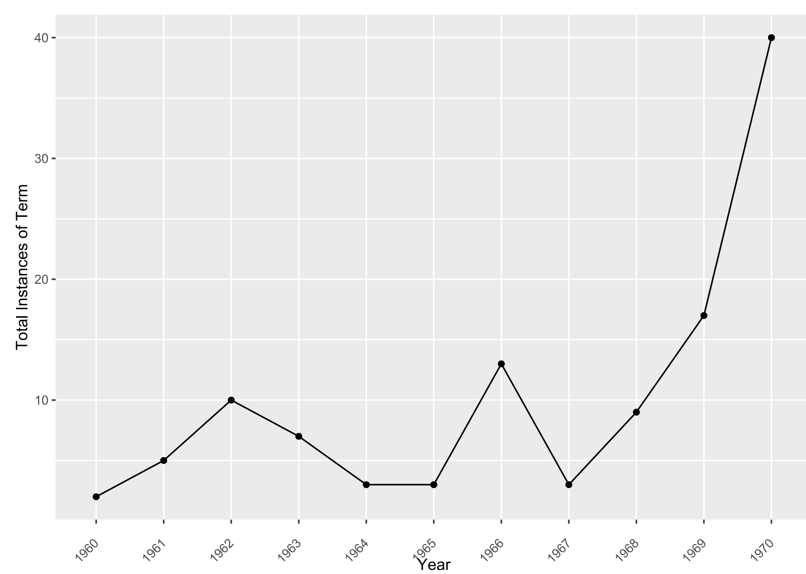
Second Movement: The “Neats” and the “Scruffies” – 1960s – 1970s

In the following section, this paper will argue that the field of AIED would be largely separated into two distinct categories following the Dartmouth workshops – the rigorous cognitivism, spearheaded by Herbert Simon and Allen Newell, and the holistic constructionism, led by Marvin Minsky and Seymour Papert. Notably, the two groups would be described as the

"neats", Simon and Newell, and the "scruffies", Minsky and Papert (Kolodner, 2002, p. 139). This description was provided based on the approach both groups would use: the "neats", Newell and Simon (1961), focused on understanding cognitive processes, such as problem-solving, emotions, or motivations, among others, through symbolic AI and highly structured rules-based processes in a careful, experimental and slow methodology to develop models of performance (Kolodner, 2002); meanwhile, the "scruffies", Minsky and Papert, focused on learning rather than performance and examined a wider range of AI, such as natural language processing, computer vision, robotics, and reasoning (Doroudi, 2023) in a "far messier approach" (Kolodner, 2002, p. 139) that attempted to understand the larger picture. Both groups of researchers would use these interpretations of AI as a representation of human thought at some level. The popularity of the research is estimated below in Figure 1, through the use of the term "Artificial Intelligence" in academic research articles.

Figure 1

Use of the Term "Artificial Intelligence" in Academic Article Titles, 1960-1970



Note: the data for this analysis was provided by Aria et al. (2024)

Cognitivism and The Neats

Herbert Simon and Allen Newell, researchers at Carnegie-Mellon University and the "neats" of AI research, would be the progenitors of the cognitivist movement in AI and AIED (Doroudi, 2023), in which tools designed to provide practical problem-solving and represent human thought patterns through information processing theories with strong roots in behaviourism (Simon & Newell, 1961). In this, the structure of research was focused on components of thought with the intention to study individual pieces of cognition in isolation (Kolodner, 2002). In cognitivism, symbolic logic would be used to provide the mechanics of AI (Simon & Newell, 1961) as well as represent the human mind (Simon, 1996); Anderson et al. (1985) would later argue that knowledge and thought could be reduced to a model and thus "human cognition appears to be a sequence of actions evoked by various patterns of knowledge" (p. 457). Some of the later researchers in this movement would emerge as Carbonell (1970), Anderson (1993, 1996; Anderson et al., 1985), and Aleven and Koedinger (2002; Koedinger et al., 2012).

Some of the first applications of this in an AIED context would be from Newell and Simon (1961) and the creation of the *General Problem Solver* (GPS) or the *Logic Theorist* application (Simon & Newell, 1970). These applications would be designed for specific purposes, such as the Logic Theorist solving theorems from Bertrand Russell's *Principia Mathematica* (Gugerty, 2006) or the GPS system as a theoretical conception of a framework to simulate human thought through symbolic logic (Newell & Simon, 1961). In this, the Newell & Simon (1961) defined an important distinction for the symbolic AI applications that would emerge from the cognitivist structure:

> It is often argued that a careful line must be drawn between the attempt to *accomplish* with machines the same tasks that humans perform, and the attempt to *simulate* the processes humans actually use to accomplish these tasks. (p. 109)

Newell and Simon would not be credited with creating the first intelligent tutoring system, but their theory of representing cognitive structure would be later used by Carbonell (1970) to do so (Doroudi, 2023).

Carbonell (1970) created an application called SCHOLAR, considered to be the first intelligent tutor, designed to review the factual knowledge of a student in the context of South American geography. This program would ask specific, factual questions, such as “The population in Chile is approx. 850000 people. True or False?” (p. 192) but could also interpret and respond to student questions such as “Tell me something about Peru” (p. 192). The contextual interpretation of language was a significant development in intelligent tutoring agents. Notably, Carbonell (1970) indicated that the SCHOLAR application did not simulate human thought, but instead this system would “produce… essentially the same output” (p. 196) as a skilled student. Later intelligent tutoring applications, however, would attempt to simulate human thought through cognition theory, such as Anderson’s (1993, 1996) *Active Control of Thought-Rational* (ACT-R) theory.

Constructionism and The Scruffies

A separate pedagogical thread emerging from the Dartmouth Conference would be carried through the “scruffies”: Marvin Minsky, who would later collaborate with Seymour Papert at the MIT Artificial Intelligence laboratory in 1964, advocated for holistic perspectives in AI and education with particular emphasis towards the LOGO programming language (Doroudi, 2023) and through the development of AI with emphasis towards microworlds. Later researchers in this field would emerge as Kahn (1977; Kahn and Winters, 1991), Schank (2016; Schank and Edelson, 1989), and Kolodner (2002).

One of the critical distinctions in the work of Minsky and Papert would be the focus on interrelationships between ideas, concepts, and cognition, rather than the emphasis on understanding those individual models of cognition (Kolodner, 2002). This would be represented

through Minsky's (1974) conceptions of micro-worlds, frames, and frame-systems. Minsky (1974) would define three central pieces of cognition: *frames*, a representation of a situation, *terminals*, data regarding the specific situation, and *frame-systems*, the inter-relationships between the different frames. In this, the author drew specific reference to the complexity of the frame-systems.

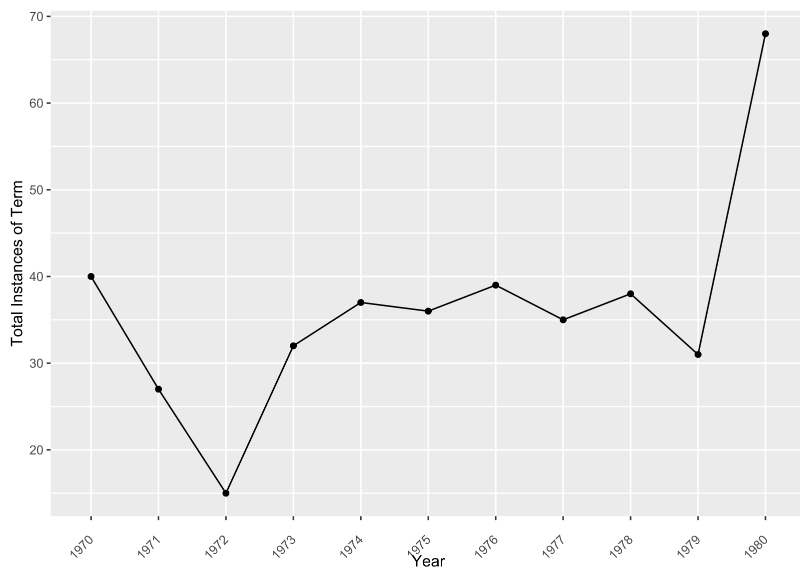
Papert (1980) was a notable theorist in education but also played a key role in his work with Minsky. Papert's (1980) work developed the *constructionist* theory of pedagogy, which would be highly related to the development of AIED and Computer-Supported Collaborative Learning. This theory was highly rooted in Piaget's *constructivism*, but developed the theory in the application towards tangible creation and experience – a hands-on and pragmatic theory of learning, distinct from Piaget's more theoretical lens (Ackermann, 2001; Papert & Harel, 1991). One of the key considerations of Papert's (1980) *Mindstorms: Children, Computers, and Powerful Ideas* was that the learner should program the computer, rather than the computer programming the learner. This position would be in opposition to the directed Intelligent Tutoring Agents proposed by the cognitivism movement.

First AI Winter: 1970 - 1980

Toosi et al. (2021) reviewed the notable "Summer" and "Winter" seasons in AI (p. 2). Following the conception of the term at Dartmouth, researchers such as Simon, Newell, and Minsky made significant claims regarding the potential of AI systems which did not materialize into productive applications. This led to a reduction of funding in the late 1960s, leading to the first AI winter, which would last until 1980 (Toosi et al., 2021). The lack of popularity of the field during this period is represented in Figure 2 below, which demonstrates a stagnation of interest in the field.

Figure 2

Use of the Term "Artificial Intelligence" in Academic Article Titles, 1970-1980



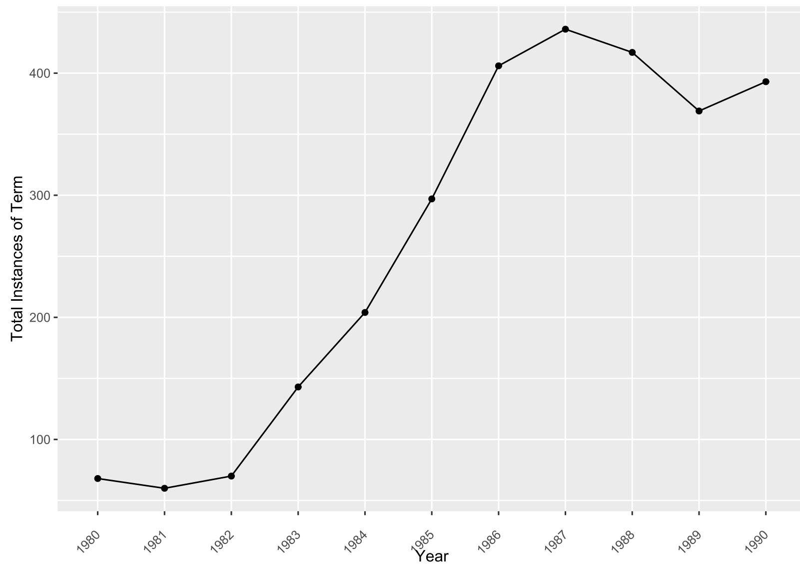
Note: the data for this analysis was provided by Aria et al. (2024)

The Birth of AIED and the Learning Sciences – 1980s-1990s

The period of the late 1980s would see a significant surge in the interest in AI as a research field. This would be referred to as the "Second Summer" (Toosi et al., 2021, p. 9) of AI in which the development of expert systems from Carnegie Mellon researchers, including notable student of Newell and Simon, John Anderson, would be very prominent (Doroudi, 2023). This is also represented through the AIED conference that would begin in 1983: the first conference would have a strong emphasis on Papert's learning environments and the LOGO programming language; the second, in 1985 had a split emphasis between Papert's learning environment and intelligent and expert tutoring systems, while the third, in 1989, had a dominant emphasis towards intelligent tutoring systems and cognitivist perspectives (Doroudi, 2023; Schank, 2016). Additionally, in 1989, the *Journal of Artificial Intelligence in Education* was published. The increase in popularity, reflected by John Self (2016), a founding editor of the journal, was "at the peak of a 'hype cycle'" (p. 5) and is represented in Figure 3 below, which demonstrates AI research had reached previously unknown levels of interest.

Figure 3

Use of the Term "Artificial Intelligence" in Academic Article Titles, 1980-1990



Note: the data for this analysis was provided by Aria et al. (2024)

Introduction of Expert Systems

Anderson (1993, 1996), who would join Newell and Simon at Carnegie Mellon in 1978 and continue the tradition of the "neats" (Doroudi, 2023), developed ACT-R theory which would create a foundation for a theory of human cognition which would be replicable through a computer. In this, Anderson (1993) declared three key features of this model: procedural and declarative distinction, knowledge complication, and strengthening. Anderson (1996) defined declarative knowledge as statements of direct fact, such as "is an addition fact" (p. 357), with procedural knowledge as functional rule statements of how to process knowledge available in declarative memory, such as "IF the goal is to add n1 and n2… [THEN] n1 + n2 = n3" (p. 357). Knowledge compilation is the process of determining declarative rules through things such as instruction-following, and strengthening refers to the development of encoding through repeated practice (Anderson, 1993). The ACT-R theory began as a model of cognition but would be realized as in the context of intelligent tutoring agents (Ritter et al., 2018).

The intelligent tutors developed by Anderson et al. (1985) made use of these rules of cognition to develop tutoring agents in mathematics sub-domains, such as geometry or LISP programming, using extensively developed rules. The agent focused on providing instruction in context, based on problem-solving, rather than lecture-based models. One of the significant listed advantages of these tutoring agents were their ability to provide immediate feedback. Later works of this would include metacognitive tutoring agents (Aleven & Koedinger, 2002) and expansion of the ACT theory into the *Knowledge-Learning-Instruction* (KLI) framework in a direct application towards educational theory (Koedinger et al., 2012). However, the dominance of the directed theory and intelligent tutoring agents would also result in a response from the “scruffies”, which would result in the creation of the learning sciences discipline.

Roger Schank and the birth of the Learning Sciences

This shift towards cognitivism in AIED directly led to the creation of the learning sciences as a field as a response, largely driven by the work of Roger Schank. Schank, a “quintessential scruffy” (Kolodner, 2002, p. 140), was originally an AI researcher, notable for his arguments towards case-based reasoning and AI learning from experience. However, he would make the shift towards education research through AI and cognitive science, coin the term *Learning Sciences,* chair the first *International Conference of the Learning Sciences*, and help form the *Journal of the Learning Sciences* in 1991 in direct response to what he considered the failures of the education system related to the use of behaviourist paradigms (Schank, 2016).

In the first year of the *Journal of Artificial Intelligence in Education*, Schank and Edelson (1989) proposed a framework of AIED which referenced a proposed educational technology that allowed students to "generate their own responses in free text...verify their answers by testing and refining them... explain their solutions rather than just identifying them" (p. 6). Notably, the authors positioned their article to combat the overemphasis of technology and the under-emphasis of theory in intelligent tutoring systems. The authors argued against systems which

coached or corrected a student when a mistake was made and instead suggested adapting the frameworks of failure-based learning or case-based learning. However, as noted earlier by Doroudi (2023) and Schank (2016), emphasis would still be placed on the intelligent tutoring systems, rather than the learning environments and their constructionist roots which Schank and Edelson (1989) advocated for here (Doroudi, 2023; McArthur et al., 2005; Schank, 2016).

Schank (2016) reflected on the development of the Institute for the Learning Sciences: in the same year, he would be given $30 million and 16 faculty to develop an institute that studied learning in a way separated from the production rules and behaviourist theory, but needed a name. He described the search for a name for his institute:

> Learning was our focus; so, learning had to be in the name of the institute. We could have called it the Institute for Learning but that sounded too much like a school. The Institute for Learning Science sounded good but if you say that out loud a few times you quickly realize that people would think we were studying how people learned science. So the Institute for the Learning Sciences was born. (p. 23)

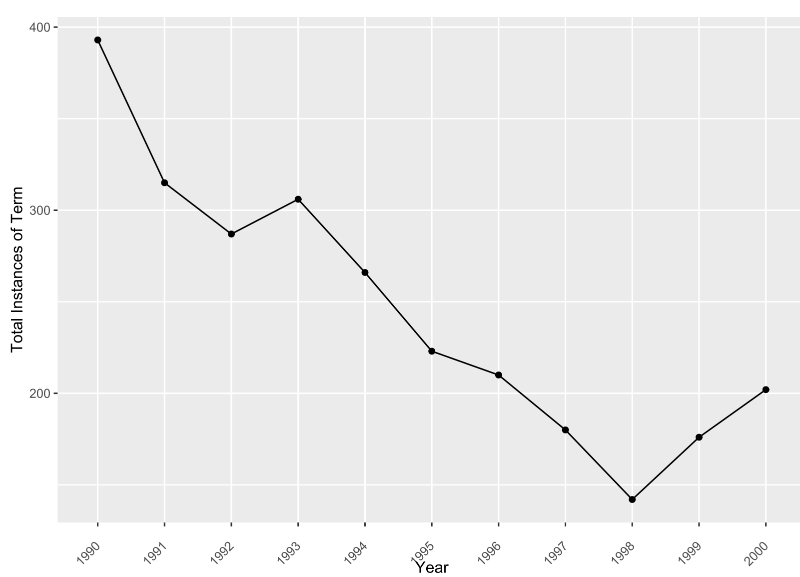
Schank (2016) furthered this through founding the *Journal of the Learning Sciences* and the International Society for the Learning Sciences in 1991 and the scheduled fifth conference of AIED, scheduled for 1991, would be re-branded into the first *International Conference of the Learning Sciences*, a change driven primarily by Schank (Doroudi, 2023). However, this rebranding would create a divergence of the fields of learning sciences, now the domain of "scruffies", while AIED, now primarily driven by knowledge-acquisition methodologies from the "neats", would re-emerge as a separate conference in 1993; this separation of thought and theory remains in place today (Doroudi, 2023).

Second AI Winter – 1990s

Nathan and Sawyer (2022) have written regarding the growth of AI from the 1960s to the 1980s and had indicated the loss of faith in AI in the 1980s as another "AI winter" (p. 32). Reflecting this, the first *Journal of Artificial Intelligence in Education* would be published in 1989 and run until 1996. One of the key considerations for the decline in interest from this period is represented through Schank’s (2016) reflection in the development of the World Wide Web, which made it possible for “training departments to spend much less money and yet appear as if they were doing something new and modern” yet resulted in “the same garbage just in a new medium” (p. 27); fundamentally, the World Wide Web represented a substitute framework for AI in the realm of technical and educative research, and the research on AI suffered as a result. The declining academic interest in AI is represented below, though examining the presence of the term “artificial intelligence” in article titles, in Figure 4 below.

Figure 4

Use of the Term “Artificial Intelligence” in Academic Article Titles, 1990-2000



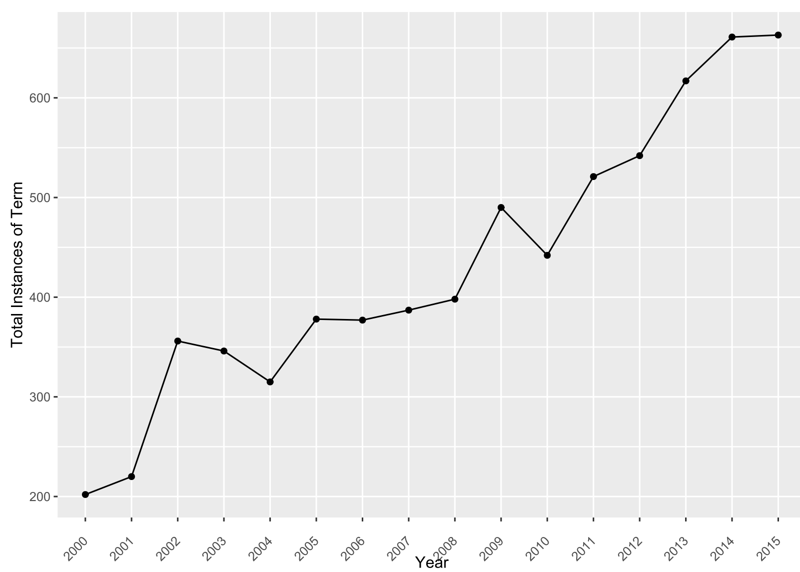
Note: the data for this analysis was provided by Aria et al. (2024)

The Information Age: 2000 – 2015

Following the lows of the second AI Winter in the late 1990s, research in AI would begin to grow again until it had passed its previous peak in the late 1980s. This would be focused again on the intelligent tutoring tools and expert systems proposed by Anderson (1985) and further developed through the work of Aleven and Koedinger (2002). In the later works of Kahn and Winters (2021), the authors wrote “there was little AI-flavoured constructionism after the 1980s until about 2017” (p. 1130) related to the divergence of the Learning Sciences and AIED in the early 90s. Additionally, learning analytics would emerge in this period as a significant method in AIED in the period (Martin & Sherin, 2013) as well as ANNs (Goodfellow et al., 2016). This period of growth is represented in Figure 5 below.

Figure 5

Use of the Term “Artificial Intelligence” in Academic Article Titles, 2000-2015



Note: the data for this analysis was provided by Aria et al. (2024)

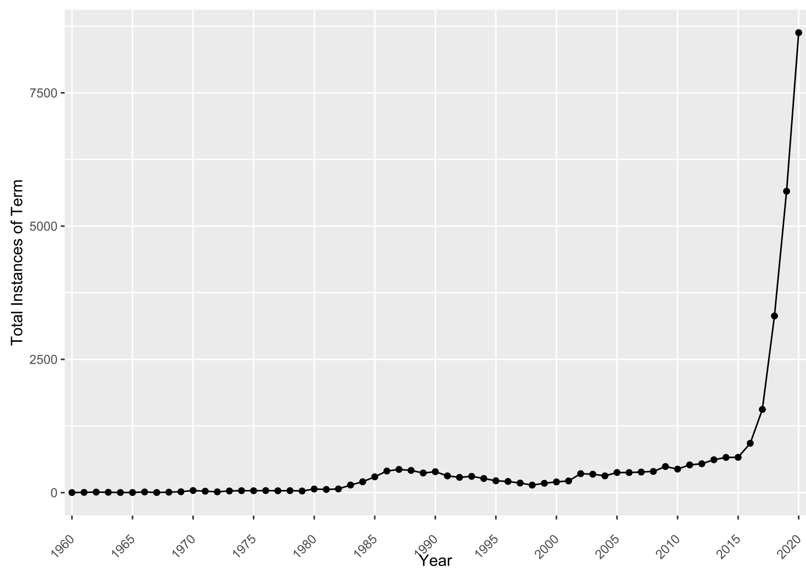
Contemporary AIED: 2016 - 2024

Leading into 2017, we observe an exponential explosion of interest around AI in academic articles. This increase is explained by Kahn and Winters (2021); the authors indicated

artificial neural networks (ANN) gained significant popularity in this period. This represents a shift in the conversation, demonstrating how different this new iteration of AI is to education; the exponential growth in the last 7 years has never been witnessed in this field before, even during the peak hype cycle in the late 1980s. We see similar patterns in data from Maslej et al. (2024) in which the publications triple in size after 2017. Figure 6 below uses the full period of analysis, 1960-2020, to demonstrate the dramatic growth observed.

Figure 6

Use of the Term "Artificial Intelligence" in Academic Article Titles, 1960-2020



Note: the data for this analysis was provided by Aria et al. (2024)

A Model of Human Intelligence: Gone but not Forgotten

Uniquely, the reflection of human intelligence through AI, which would be present, though with some fundamental distinctions, in the paradigms of both the "neats" (Simon and Newell, 1970; Carbonell, 1970; Anderson, 1985) as well as the "scruffies" (Minsky, 1971; Papert, 1980; Schank, 2016) had all-but-disappeared from the conversation of AIED in contemporary research, largely due to the emergence of ANNs. In a historical analysis of theories and application in AIED, Rismanchian and Doroudi (2023) identified that between initial

AIED conferences in the 1985 and 1993 compared with the published papers in 2021 that the use of AI to represent human intelligence was removed from the discourse. Notably, Rismanchian and Doroudi (2023) found greater diversity in the earlier proceedings of AIED in 85/93; papers and presentations drew on tools such as ITS but also indicated that a significant proportion of papers analyzed AI as an analogy to human intelligence. However, in the papers analyzed in 2021, from AIED and IJAIED, all but one paper drew on concepts related to AI as an applied tool. The majority of articles focused on either researcher interaction, such as learning analytics, or at applied tools, such as tutoring systems.

This shift in the foundations of AIED can also be examined through the technical foundations underlying the development of AI in each period and specifically the movement from symbolic models to artificial neural networks (Mohammed et al., 2024). A highly popular intelligent tutoring system in the 1980s, the *LISP Tutor*, reflected the earlier development of AI models as representations of existing models of thought using symbolic logic models. This framework was used to “represent the rules programmers have for solving problems” (Anderson & Reiser, 1985, p. 160) in an effort to replicate a human-based problem-solving method. Through the provided examples, this tutor followed a very specific, step-by-step problem-solving process to teach the student to code, often examining individual lines of code and providing specific instruction or question related to each use case. This symbolic language model was not dissimilar from traditional instructional methods. However, during the 1980s, ANNs, or deep learning, began gaining popularity as computational power, and therefore training power, also rose (Mohammed et al., 2024).

The original conceptualizations of artificial neural networks were inspired by the neural connections observed in the human brain and largely based on advances in cognitive sciences (Goodfellow et al., 2016; Worden et al., 2023). Rather than models which attempted to provide a robust definition of thought patterns, such as Anderson & Reiser’s (1985) *LISP Tutor*, ANNs

attempted to replicate the wiring of the human brain through connected neurons. However, these models would diverge from neuroscience and instead draw from theories of mathematical optimization, such as the fields of linear algebra, probability, or information theory (Goodfellow et al., 2016). Notably, ANN models had existed prior to this period (Minsky & Papert, 1988), but both increasing dataset size and computational power provided the necessary means for these models to demonstrate problem-solving capabilities (Goodfellow et al., 2016). Deep learning became concerned with developing computer programs that could solve problems that required some form of intelligence.

This shift in emphasis in deep learning and artificial intelligence represented a significant change in the discussions regarding AIED and how it could be applied in a systematic context. The mathematical models of AI no longer represented a pedagogical or psychological approach, and research focused on using AI in a more pragmatic manner. This shift reflected the prescient distinctions of Newell & Simon (1961) between the attempt to "accomplish with machines the same tasks humans perform" or to "simulate the processes humans actually use" (p. 109). The processes, as reflected through pedagogical or psychological models, became less relevant through ANNs.

The shift in research emphasis is further demonstrated through contemporary meta or systematic analyses of contemporary AIED, including in the period after the public launch of ChatGPT. Zawacki-Richter et al. (2019) found that the primary uses of AIED identified by researchers were prediction and learning analytics, intelligent tutoring systems, and assessment and evaluation. In a later meta-systematic review, Bond et al. (2024) confirmed that the primary identified benefit of AIED was related to applied tools, as either learning or teaching focused tools, such as personalized learning, intelligent tutoring, or assessment and evaluation, or researcher or administrative-focused tools, such as profiling and prediction. These uses of AI represent the use of AI as an applied tool, rather than a perspective into understanding human

cognition.

This theoretical change is a foundational change and represents how we have come to think about these AI systems. Despite the technology available to the researchers in the earlier periods, they viewed AI as a precursor to human intelligence – that they were building models of thought, rather than machines. In contemporary research, despite the incredible features of generative AI, it remains a "stochastic parrot" (Bender et al., 2021), a statistical machine that repeats words based on probability, not on understanding – in words of Cukurova (2024): "intelligence is more than that" (p. 2). We have changed the way we interpret these machines and applications: AI is now a model of performance, rather than also a tool to allow for introspection into human cognition. This shift towards pragmatic application in AIED has provided significant benefits, such as the rapid development of educational technology supporting adaptive or personalized learning; however, this shift also represents a movement away from traditionally informed methods of pedagogy and their incorporation into AIED. Further research is required to investigate how these pragmatic applications affect long-term and higher-order thinking skills, such as critical thinking and metacognition.

Despite this foundational shift towards performance, there is representation of constructionist lens in AIED research which represents Papert's (1980) vision that the "child programs the computer" (p. 5). For example, Castro et al. (2022) used AI in the context of dance in which learners could engage with these tools to assist with animation related to body movement; Ali et al. (2023) developed a curriculum in which learners used the image generation functionality of ChatGPT to build representation of their own dreams, and Morales-Navarro et al. (2024) allowed learners to code with an emphasis on debugging, or learning from failure, in the context of wearable electronic textiles. There are additional debates around this topic, such as Shneiderman (2020) or Cukurova (2024) advocating for a high degree of human agency when working with AI automation in AIED. Ultimately, a balanced approach between the current

modes of pragmatism and previous models of cognitive process must be further incorporated into AIED to balance both immediate learning outcomes and longer-term and higher-order processes. However, there is still a need for more research which applies a constructionist paradigm in AIED research.

Limitations

There are limitations in this study related to time and scope. Given the narrative review methodology of this literature, further systematic research could provide a more robust analysis on the distinct periods and contemporary developments of AI and the learning sciences. Additionally, this narrative review was designed for breadth and scope to review multiple perspectives over the past 70 years, but was not designed for depth; this may create inaccuracies or surface-level representations of the complex theories of the past. As well, this review focused specifically on the concepts of the learning sciences, constructionism, and cognitivism in the context of AIED. There are other distinct theories and work which could provide valuable insight, such as behaviourism, that are not discussed in this analysis.

Conclusion

This study has examined the growth of AI and education through the lens of the two major theoretical lenses, cognitivism and constructionism, and argued that the initial growth in AI research was specifically related to the development of both cognitive and learning theory, and it would lead directly to the development of the learning sciences as a field.

The histories of AI and AIED have been summarized through several periods with emphasis on the seminal scholars in each period with respect to their situated perspectives within the “neat” or “scruffy” paradigms of research. Additionally, the “summer and winter” or “hype-cycles” of AI have been observed twice in the past in which significant interest is garnered, funding obtained, promises made, but often undeliverable through the available technology. While it is not necessarily the case that another AI winter will follow this exponential increase in interest, several industry experts have expressed doubts regarding current

architecture, such as Yann LeCun, chief AI scientist at Meta and seminal researcher in deep learning, who predicted there would be “absolutely no way” (Wodecki, Feb 8th, 2024, para. 15) to reach human-level intelligence with current large-language models and their underlying architecture, while others have warned of model collapse and exhausting existing data sources (Shumailov et al., 2024). Despite the promises of and interest in generative AI and LLMs, it is not impossible for a new AI winter to emerge.

Ultimately, this paper advocates for a return and further connection between the learning sciences with the study of AIED in the face of the disruption created by generative AI tools such as ChatGPT. The adaptation of constructionist models in AIED, where high learner agency is maintained, has the potential to significantly enhance the learning associated with AIED and ensure the learner’s experience remains as a central point of focus. This paper calls for further research into the re-integration of these methods to explore how these paradigms can be adapted into modern contexts in order to build theories, frameworks, and curriculum which support the long-term development of learners in an AI-assisted, rather than AI-driven, society.

References

Ackermann, E. (2001). Piaget's Constructivism, Papert's Constructionism: What's the difference? *Constructivism: Uses and Perspectives in Education*, *5*(3), 85–94.

Aleven, V. A. W. M. M., & Koedinger, K. R. (2002). An effective metacognitive strategy: Learning by doing and explaining with a computer-based Cognitive Tutor. *Cognitive Science*, *26*(2), 147–179. https://doi.org/10.1207/s15516709cog2602_1

Ali, S., DiPaola, D., Williams, R., Ravi, P., & Breazeal, C. (2023). *Constructing dreams using generative AI* (arXiv:2305.12013). arXiv. https://doi.org/10.48550/arXiv.2305.12013

Anderson, J. R. (1996). ACT: A simple theory of complex cognition. *American Psychologist*, *51*(4), 355–365. https://doi.org/10.1037/0003-066X.51.4.355

Anderson, J. R., Corbett, A. T., Koedinger, K. R., & Pelletier, Ray. (1995). Cognitive tutors: Lessons learned. *Journal of the Learning Sciences*, *4*(2), 167–207. https://doi.org/10.1207/s15327809jls0402_2

Anderson, J., Boyle, C. F., & Reiser, B. (1985). Intelligent tutoring systems. *Science (New York, N.Y.)*, *228*, 456–462. https://doi.org/10.1126/science.228.4698.456

Anderson, J. R., & Reiser, B. J. (1985). The LISP tutor. *Byte*, *10*(4), 159-175.

Aria, M., Le T., Cuccurullo, C., Belfiore, A. & Choe, J. (2024). openalexR: An R-Tool for Collecting Bibliometric Data from OpenAlex, The R Journal, 15(4), 167-180. https://doi.org/10.32614/RJ-2023-089.

Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? □. *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, 610–623. https://doi.org/10.1145/3442188.3445922

Carbonell, J. R. (1970). AI in CAI: An artificial-intelligence approach to computer-assisted instruction. *IEEE Transactions on Man-Machine Systems*, *11*(4), 190–202. IEEE Transactions on Man-Machine Systems. https://doi.org/10.1109/TMMS.1970.299942

Castro, F. E. V., DesPortes, K., Payne, W., Bergner, Y., & McDermott, K. (2022). AI + Dance: Co-designing culturally sustaining curricular resources for AI and ethics education through artistic computing. *Proceedings of the 2022 ACM Conference on International Computing Education Research - Volume 2*, *2*, 26–27. https://doi.org/10.1145/3501709.3544275

Cukurova, M. (2024, April 5). *The interplay of learning, analytics, and artificial intelligence in education* [Working / discussion paper]. CoRR; arXiv. https://discovery.ucl.ac.uk/id/eprint/10191279/

Doroudi, S. (2023). The intertwined histories of artificial intelligence and education. *International Journal of Artificial Intelligence in Education*, *33*(4), 885–928. https://doi.org/10.1007/s40593-022-00313-2

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning.* MIT Press. https://www.deeplearningbook.org/

Gugerty, L. (2006). Newell and Simon's Logic Theorist: Historical background and impact on cognitive modeling. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *50*, 880–884. https://doi.org/10.1177/154193120605000904

Kahn, K., & Winters, N. (2021). Constructionism and AI: A history and possible futures. *British Journal of Educational Technology*, *52*(3), 1130–1142. https://doi.org/10.1111/bjet.13088

Kahn, K. (1977). Three Interactions between AI and Education. *Machine Intelligence*, *8*, 422–429.

Koedinger, K. R., Corbett, A. T., & Perfetti, C. (2012). The Knowledge-Learning-Instruction framework: Bridging the science-practice chasm to enhance robust student learning. *Cognitive Science*, *36*(5), 757–798. https://doi.org/10.1111/j.1551-6709.2012.01245.x

Kolodner, J. L. (2002). The “Neat” and the “Scruffy” in promoting learning from analogy: We need to pay attention to both. *The Journal of the Learning Sciences*, *11*(1), 139–152.

Martin, T., & Sherin, B. (2013). Learning Analytics and Computational Techniques for Detecting and Evaluating Patterns in Learning: An Introduction to the Special Issue. *Journal of the Learning Sciences*, *22*(4), 511–520. https://doi.org/10.1080/10508406.2013.840466

Maslej, N., Fattorini, L., Perrault, R., Parli, V., Reuel, A., Brynjolfsson, E., Etchemendy, J., Ligett, K., Lyons, T., Manyika, J., Niebles, J. C., Shoham, Y., Wald, R., & Clark, J. (2024). *The AI index 2024 annual report*. AI Index Steering Committee, Institute for Human-Centered AI, Stanford University. https://aiindex.stanford.edu/report/

McCarthy, J., Minsky, M., Rochester, N., & Shannon, C. (1955). *A proposal for the Dartmouth Summer Research Project on artificial intelligence*. https://raysolomonoff.com/dartmouth/boxa/dart564props.pdf

Minsky, M. & Papert, S. (1988). *Perceptrons: An introduction to computational geometry.* Massachusetts Institute of Technology.

Mohammed, A. T., Velander, J., & Milrad, M. (2024). *A Retrospective Analysis of Artificial Intelligence in Education (AIEd) Studies: Perspectives, Learning Theories, Challenges, and Emerging Opportunities*. https://doi.org/10.1007/978-981-97-8638-1_9

Morales-Navarro, L., Fields, D. A., Barapatre, D., & Kafai, Y. B. (2024). Failure artifact scenarios to understand high school students’ growth in troubleshooting physical computing projects. *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 1*, 874–880. https://doi.org/10.1145/3626252.3630855

Nathan, M. J., & Sawyer, R. K. (2022). Foundations of the Learning Sciences. In R. K. Sawyer (Ed.), *The Cambridge Handbook of the Learning Sciences* (3rd ed., pp. 27–52). Cambridge University Press. https://doi.org/10.1017/9781108888295.004

Newell, A., & Simon, H. A. (1961). GPS, a program that simulates human thought. In *Readings in Cognitive Science* (pp. 453–460). Elsevier. https://doi.org/10.1016/B978-1-4832-1446-7.50040-6

Papert, S., & Harel, I. (1991). Situating constructionism. In I. Harel & S. Papert (Eds.), *Constructionism* (pp. 1-17). Ablex Publishing Corporation.

Papert, S. (1980). *Mindstorms: Children, computers, and powerful ideas.* Basic Books Inc.

Rismanchian, S., & Doroudi, S. (2023). Four interactions between AI and education: Broadening our perspective on what AI can offer education. In N. Wang, G. Rebolledo-Mendez, V. Dimitrova, N. Matsuda, & O. C. Santos (Eds.), *Artificial Intelligence in Education. Posters and Late Breaking Results, Workshops and Tutorials, Industry and Innovation Tracks, Practitioners, Doctoral Consortium and Blue Sky* (pp. 1–12). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-36336-8_1

Schank, R. C. (2016). Why Learning Sciences? In M. J. Packer, M. A. Evans, & R. K. Sawyer (Eds.), *Reflections on the Learning Sciences* (pp. 19–31). Cambridge University Press. https://doi.org/10.1017/CBO9781107707221.002

Schank, R., & Edelson, D. (1989). A role for AI in education: Using technology to reshape education. *Journal of Artificial Intelligence in Education*, *1*(2), 3–20.

Self, J. (2016). The birth of IJAIED. *International Journal of Artificial Intelligence in Education*, *26*(1), 4–12. https://doi.org/10.1007/s40593-015-0040-5

Shneiderman, B. (2020). Human-Centered artificial intelligence: Reliable, safe & trustworthy. *International Journal of Human–Computer Interaction*, *36*(6), 495–504. https://doi.org/10.1080/10447318.2020.1741118

Shumailov, I., Shumaylov, Z., Zhao, Y., Papernot, N., Anderson, R., & Gal, Y. (2024). AI models collapse when trained on recursively generated data. *Nature*, *631*(8022), 755–759. https://doi.org/10.1038/s41586-024-07566-y

Simon, H. A. (1996). *The sciences of the artificial* (3. ed., [Nachdr.]). MIT Press.

Toosi, A., Bottino, A. G., Saboury, B., Siegel, E., & Rahmim, A. (2021). A brief history of AI: How to prevent another winter (A critical review). *PET Clinics*, *16*(4), 449–469. https://doi.org/10.1016/j.cpet.2021.07.001

Turing, A. (1950). Computing machinery and intelligence. *Mind*, *59*(236), 433–460.

Williamson, B., & Eynon, R. (2020). Historical threads, missing links, and future directions in AI in education. *Learning, Media and Technology*, *45*(3), 223–235. https://doi.org/10.1080/17439884.2020.1798995

Wodecki, B. (2024, February 8). *Meta's Yann LeCun wants to ditch generative AI*. https://aibusiness.com/nlp/meta-s-yann-lecun-wants-to-ditch-generative-ai

Worden, K., Tsialiamanis, G., Cross, E. J., & Rogers, T. J. (2023). *Artificial Neural Networks*. https://doi.org/10.1007/978-3-031-36644-4_2

Appendix A: R Code for creating OpenAlex graphs

In an effort to ensure reproducible research, the following is the code used in R to create the OpenAlex graphs used in this study. To modify the scope of the graph, the dates in line 22 should be changed.

```
require(openalexR)
require(tidyverse)
require(magrittr)
require(nplyr)

works_search <- oa_fetch(
entity = "works",
title.search = c("artificial intelligence"),
type = 'article',
from_publication_date = "1960-01-01",
to_publication_date = "2024-12-31",
options = list(sort = "cited_by_count:desc"),
verbose = TRUE
)

research_df <- works_search %>%
mutate(year=format(as.Date(publication_date), '%Y')) %>%
filter(type=='article') %>%
group_by(year) %>%
summarize(total=n())

research_df %>% filter(between(year, '1960', '2020')) %>%
ggplot(aes(x=year, y=total, group=1)) +
geom_point() + geom_line() +
theme(axis.text.x = element_text(angle = 90, vjust = 0.5,
hjust=1))
```